A PROBABILISTIC MODEL FOR ASSESSING ENERGY CONSUMPTION OF THE NON-DOMESTIC BUILDING STOCK

Ruchi Choudhary
Energy Efficient Cities Initiative
Department of Engineering, University of Cambridge, UK

ABSTRACT
This paper presents a probabilistic framework for developing energy models of the built environment in a city and demonstrates its first-phase application to non-domestic buildings in Greater London. The work is driven by the need to quantify future energy demand of buildings in their urban context as a function of projected growth of buildings and populations, refurbishments, policies incentivizing energy efficiency measures, and changes in building operation. The focus on the non-domestic sector enables exploring a framework that accommodates diverse set of activities and uses of buildings within an urban region.

INTRODUCTION
Techniques for extending building level models to quantify net energy demand of a neighborhood, district, or city region have come into closer scrutiny as policy-implementers are under pressure to take actions for reducing energy consumed by regions or districts as a whole. A larger quantity of published literature on this topic deals with the domestic building stock, primarily because it is the dominant overall consumer of energy within the building stock and will hence play a critical role in meeting overall carbon-reduction targets set by governments. A secondary reason is that overall assessment of non-domestic sector is often infeasible or difficult due to the sheer diversity of use, activities, and ownership structures within it. Notable studies that have contributed towards modeling and analyzing the non-domestic sector are: A district clustering approach implemented for Osaka City (Yamaguchi et al., 2007), based on dynamic simulation of each building in a district, where a district is associated with a dominant representative building type, (b) The N-DEEM model in the UK (Pout et al., 1998, 2002) supported by extensive energy audits of a large sample of buildings in the UK by Mortimer et al. (1999) and by the development of non-domestic data base (NDBS) by Bruhns et al. (2000); Steadman et al. (2000). The authors of NDBS have recently extended their work by mapping UK’s energy and property data within a comprehensive framework (Bruhns and Wyatt, 2011) and proposed its use for informing energy-efficiency policies. Jones et al. (2000) developed an energy and environmental prediction (EEP) model, in which the non-domestic sub model uses energy benchmark values in conjunction with available datasets of property types. A time-varying energy consumption model for the US commercial stock by Coffey et al. (2009) is based on the Commercial Buildings Energy Consumption Survey (CBECS) developed by the US Energy Information Administration (EIA).

A common feature in these studies is that the energy consumption of a set of uniform buildings within an area is normalized and expressed as kWh/m^2/year. This value, referred as energy use intensity (EUI), is either derived from published standards of typical building consumption patterns, from auditing energy consumption of a representative sample of buildings, or computed using statistical or physics-based energy models of representative buildings. It is a standard normalization because it enables scaling-up energy consumption of a large set of buildings into gross energy consumption of a district, and likewise, allows delegating total energy use of a district to its consumers (buildings). Indeed, it is reasonable to assume that a set of office buildings located in the same area, with similar activities will consume roughly the same amount of energy per unit of floor area. The case of this form of standardization based on building use rather than its construction and physical characteristics is strong in the context of non-domestic buildings where variability in energy consumption between two buildings is dominated by the demand for activity related services (Prez-Lombard et al., 2008). Thus, primary classification of non-domestic buildings generally follows its function. For example, the N-DEEM model is based on 10 primary categories of non-domestic buildings and Bruhns and Wyatt (2011) base their study on 13 bulk types. The primary classes are attributed to an expected value of EUI, but sometimes they are derived by aggregating EUI of sub-categories. For example, the primary category of health comprises of surgeries, health centers, nursing homes, and hospitals. In a different approach, Coffey et al. (2009) sub-categorize buildings based on age and maintenance quality of a building. The point to be made here is that the EUI of a primary category is not only representative of a large set of buildings that have similar function, but also incorporates subcategories of buildings that have heterogeneous energy consumption patterns. Hence the EUI...
of a building is best expressed as a probability distribution function (pdf) incorporating the uncertainties around its expected value. In this case, by definitions found in Spiegelhalter and Best (2003), the probability distribution will quantify the first order or aleatory uncertainties arising from variability of energy use in primary categories due to its sub-categories and also the chance variation among individual sub-categories due to differences in maintenance, age, installed technologies, and building specific characteristics. This paper presents a modeling framework based on Bayesian Inference for quantifying these uncertainties and deriving probability distributions of energy use for primary categories of non-domestic buildings in Greater London.

**MODELLING FRAMEWORK**

In the most simple and idealized, the total energy consumption of buildings in a district can be expressed as the sum total of energy consumption of its constituent buildings in the following form:

\[ E_k = \sum_{i=1}^{N} \text{EUI}(i) \text{PA}(i,k) + \varepsilon_k \]  

(1)

where \( E_k \) is the total energy consumption of a district \( k \) in kWh/m²/year, normalized by its total built area. \( \text{EUI}(i) \) is the energy use intensity of a primary building type \( i \) in kWh/m²/year, \( \text{PA}(i,k) \) is the percentage of built floor area of building type \( i \) in district \( k \), and \( N \) is the total number of primary building types. Where more detailed categorization of buildings is accessible, the function can be extended to include the energy use intensities of sub-categories \( l \) in a primary type \( i \) as:

\[ \text{EUI}(i) = \sum_{l=1}^{n_{subt}} \text{EUI}_l(l) \text{PA}_{i,k}(l) \]  

(2)

where \( \text{PA}_{i,k}(l) \) is the percentage area of sub-category \( l \) of building type \( i \) in district \( k \). The term \( \varepsilon_k \) is an error term, accommodating any differences between the recorded gross energy consumption of a district and that of its individual buildings. These errors may be systematic, owing to how energy is recorded at district scale exogenous to buildings (non-building energy consumption). If the total built area per building type of a district and their respective EUI at a current time-period were known, equation 1 & 2 could be used to compute relative changes in total energy use due to projected future growth in built area of a certain type in a district and/or due to improvements in energy use intensity of certain types of buildings in a district.

To construct the model for the current time-period, one would ideally need true values of gross internal area and EUI for every single building in a district, which is generally prohibitive. In the case of London, availability of Geographic Information Services maps and records held by the Valuation Office Agency (VOA) means that area information is in principle more accessible\(^1\). EUI per building is more uncertain since it cannot be accessed or computed on a building by building basis, especially when large districts or entire extent of city needs to be evaluated. Values of EUI published in CIBSE (2008) are representative average of typical UK buildings, and the extent to which they deviate in reality is not known.

On the other hand, the UK government’s Department of Energy and Climate Change (DECC) releases annual energy statistics for local authority (LA) and middle layer super output areas (MLSOA) levels\(^2\) covering electricity, gas, and total energy consumption. For Greater London, total annual energy consumption \( E_k \) of non-domestic buildings is thus available for its constituent 33 LAs and 1049 MLSOAs. The dataset does not disclose information of large non-domestic consumers at MLSOA level and thus the most complete information is available only at the LA level.

Since total energy consumption \( E_k \), total built area, and percentage areas \( \text{PA}_{i,k} \) per building type \( i \) are known for the 33 London Authorities in Greater London, the EUI, for \( N \) building types could be estimated using a linear regression model if the number of building types \( N \) were much less than the total number of districts \( D \). However, even the most broad categorization of non-domestic buildings results in at least 10 different building types: the N-DEEM model (Pout et al., 2002) identifies 10 primary building types and Bruhns and Wyatt (2011) list 13 primary classifications of non-domestic buildings. To overcome the challenges of incomplete and uncertain information, we use Bayesian regression to estimate the EUIs of non-domestic buildings in London. This helps us constrain the EUI of buildings on the basis of prior beliefs and naturally accounts for uncertainties in their values. These prior beliefs are a combination of empirical evidence (e.g. from display energy certificate data) and typical values reported in CIBSE (2008). They are assembled into a probability distribution function (pdf) for the EUI of each building type included in the model. The priors on the EUI must reflect plausible values of EUI: they have to be positive and within a range of values specific to the building type. Beta distributions are suitable because they can be defined on the interval \((0,1)\), and parameterized by two positive shape parameters denoted by \( \alpha \) and \( \beta \). Thus, prior distributions of EUI for every building type \( i \) are given as:

\[ \text{EUI}(i) = B_i(\alpha, \beta), \quad i = 1, \ldots, N \]  

(3)

Unlike standard regression, the EUIs are estimated by updating information from the priors with the in-
formation contained in the data. We use WinBUGS (Lunn et al., 2000; Spiegelhalter et al., 2003) to carry out the Bayesian regression. WinBUGS is a software based on Markov chain Monte Carlo (MCMC) methods for Bayesian probability models. As a result of the Bayesian analysis we obtain probability distributions of the estimates of the EUIs (called posteriors). The following section describes the parametrization of this model in more detail.

MODEL PARAMETERS

Area Calculations

Area estimates per building usage for London are available from the Valuation Office Agency (VOA), and from commercial mapping databases. This particular study uses a GIS database called UKMap, which provides building use compatible with national land use categories (NLUD 4.4) and footprint area for every building in London. Figure 1 shows that the UKMap land use data matches the generalized land use data (GLUD) published by ONS Neighborhood Statistics and DCLG: Some discrepancy is expected because the two are created independent of one another. Furthermore, the GLUD database provides 2005 figures and the UKMap dataset was released in 2010, and is hence more recent. UKMap database is suitable for the current study because it also includes information of building heights and usage above retail, which is a common feature in London. The total built area per building type is estimated by dividing the given height of the building footprint by typical values of floor height per building type. Typical floor heights of buildings in a city can vary due to their function, total height, construction type, and footprint area. They are taken from published architectural standards.

Categorization of non-domestic buildings is based on identifying buildings with similar energy consumption characteristics as sub-categories, and then pooling together sub-categories based on sectoral definition of services provided as primary types. These are listed in table 1 along with their total percentage share of the non-domestic built area. The percentage area per building type calculated for each local authority ($P_{A_{i,k}}$) is shown in figure 2. These values are input into the Bayesian regression model as 'known' information.

Energy Use Intensity

Energy Use Intensity of a building should be ideally separated explicitly by the form in which it is delivered to a site: thermal (direct fuel use) and electricity. If the source is known, they can be combined via more comparable factors. For example, in terms of CO$_2$ emissions, or monetary costs. In this study, they are summed together as a notional value to represent total energy consumed per area of a building in the unit kWh. The reason for combining these two forms of energy consumption is to accommodate buildings that are all-electric. Without combining gas and electricity use, we would have some buildings within a sector that have very high electricity use intensity. Furthermore, we would need to define multi modal distributions to represent the collection of similar type of buildings that differ in their direct fuel consumption: (a) some

---

3A detailed account of these and other sources of built area is given in Bruhns and Wyatt (2011)

4from The Geoinformation Group

Details on this aspect of the work are not shown in this paper. They will be presented more fully in a later, more extended publication.
that use no fuel, (b) some that use a small proportion of fuel (e.g., for water heating only), and (c) others that rely on fuel for all their heating needs.

The mean or typical values of this notional EUI can be taken from CIBSE (2008), but their distribution around this value is highly uncertain. For reasons explained earlier in the paper, we define prior estimates of EUI per primary type of non-domestic buildings as beta distributions in the form shown in equation (3). We do not have sufficient number of observations to be able to derive EUI distributions from the Bayesian regression model without supporting it with very plausible prior estimates. Therefore, all available empirical information is pooled to define prior pdfs around the expected values of EUI per building type. Two sets of values define the prior distributions of EUIs: (a) plausible upper and lower limits of EUI corresponding to the normalized interval (0,1) of the beta distribution, and (b) shape parameters of the beta distribution (\(\alpha\) and \(\beta\)).

The Centre for Sustainable Energy has recently released full Display Energy Certificate (DEC) register dataset for all UK public buildings from the Department of Communities and Local Government (DCLG) covering registers from 2008 onwards. This dataset contains EUI, floorspace, building use, and full postcode of 40,000 public buildings of over 1,000m\(^2\) in England and Wales, of which 3,220 buildings are in London\(^6\). Figure 3 shows the distribution of EUI as reported in this dataset for 436 public-sector offices, 1363 educational buildings, 274 hospitals, and 344 community buildings in London. Distributions of EUI for categories of Primary Care, Sports, Arts were derived from the same dataset (not shown here). We fit a beta distribution to these histograms to derive the upper and lower limits of EUI values. This dataset, however, does not cover private sector offices, retail, hotels, and industrial buildings.

In addition to the DEC dataset, the DCLG was able to provide Energy Performance Certificate (EPC) registers for 28,370 non-domestic buildings within Greater London along with their primary use and partial post code. An EPC is required for any non-domestic building greater than 50 m\(^2\) undergoing construction, modification, sale or lease. This dataset hence covers private-sector buildings. Unlike DEC, EPC of buildings are not based on their actual measured energy consumption. Instead, they are based on a theoretical calculation of their carbon emissions, summarized via ‘asset rating’. The asset rating is a useful indicator for comparing a building relative to another of the same type or its expected benchmark, but does not correspond to its actual energy consumption. Figure 4 show the distribution of asset ratings for 17,108 retail shops and 210 hotels in London. We assume that the median asset rating roughly corresponds to the typical EUI of hotel, retail, and industrial buildings reported in CIBSE (2008) and CIBSE (2004). As a result, we are able to come up with the spread of their EUI. For example, the median asset rating for the hotel from this dataset is 79. Fitting a beta distribution on the pdf of the asset rating gives us upper and lower limits of

---

\(^{6}\)www.cse.org.uk/pages/resources/open-data
asset ratings to be 135 and 35 respectively. Given that
the mean asset rating corresponds to 435 kWh/m²/year
(typical EUI of hotel reported in CIBSE (2008)), we
are able to compute the upper and lower limits of EUI
of hotels to be 740 and 190 kWh/m²/year.

Three sets of priors were employed as potential EUI
distributions. This lead to running the Bayesian model
with three overlapping, but very different prior esti-
mates in terms of the shape of the distributions:

1. Prior Estimates 1: For the first set, we assume that
the shape of the distributions of EUI closely fol-
low the variations in the samples from DEC and
EPC reports. The shape parameters are derived
by fitting beta distributions to the samples shown
in Figure (3, 4). We call these empirical priors

2. Prior Estimates 2: In the second set, we suggest
that the median value of the EUI derived from the
DEC and EPC dataset is perhaps better representa-
tive of the most likely value of EUI. Therefore,
the shape parameters are ascribed such that the
distribution is symmetrical and narrow around the
median values of EUI. These are called estimated
priors.

3. Prior Estimates 3: In the final scenario, we give
relatively more uninformative priors. We suggest
that the most likely value of EUI is located ex-
actly in the middle of the upper and lower limits
derived from DEC and EPC dataset. We impose
symmetric shapes around this center value and a
more uniform spread than in previous cases. We
call these uninformative priors.

Table 2 shows the shape parameters of these three prior
distributions. Prior estimates 2 & 3 are the same for the
private sector buildings since we do not have an em-
pirically derived median value of EUI in these cases.
Table 2 also lists the limits of the beta distribution and
the median values of EUI derived either from the DEC
dataset (in the case of public-sector buildings) or from
CIBSE (2008) for the private-sector buildings.

Figure 3: EUI of public-sector buildings in London as reported in DEC register

Figure 4: Asset Rating of Hotels and Retail Buildings in London as reported in the EPC register

Energy Data
As mentioned in the earlier section, the lowest usable
resolution of non-domestic energy consumption data
is available at the local authority (LA) level. The UK
Department of Energy and Climate Change (DECC)
releases this information annually since 2005. We use
the 2008 data since it is the most recent and the areas
are calculated from a dataset compiled recently and
released in 2010 (by UKMap). Figure 5 shows the
2008 total energy consumption by local authority. As
a preliminary test of the influence of EUI values on
gross energy consumption, we compare these values
with calculated energy consumption if median values
of EUIs (listed in table 2) were to be used to calculate
the energy consumption of each LA. As shown, the use
of median values of EUI would result in underestimat-
ing the gross energy consumption of most LAs.

Error Terms
We introduce the error term $\varepsilon_k$ in equation 1 to accom-
modate factors that may lead to lack of fit between the
model and observations. Indeed, we do not know the
extent to which the model and observations deviate.
Potential reasons for the deviations are the ways in
which energy consumption data is measured, or how
it is aggregated by DECC. The calculation of built
area per building type may also not be totally accurate.
Thus, the error term $\varepsilon_k$ is included as an additional un-
certain parameter in the Bayesian model. We do so by
specifying the total energy consumption of an LA, $E_k$
as a normal distribution with an uncertain standard de-
viation. As standard in these formulations, the inverse
of the standard deviation of $E_k$, called precision, fol-
ows a Gamma distribution. This parameter allows for
large uncertainties in observed energy consumption to
be accommodated.

We should also mention that one of the main underly-
ing assumptions in this model is that EUI of a building
type $i$ is uniform across all areas of Greater London.
It is a reasonable assumption since the units of analy-
ses are contained within the same city. In reality, EUIs
of a building may differ from one LA to another due
Table 1: Primary types of non-domestic buildings with their constituent sub-types and percentage share of total non-domestic built area in London

<table>
<thead>
<tr>
<th>Primary Type</th>
<th>% Area</th>
<th>Sub-Types</th>
</tr>
</thead>
<tbody>
<tr>
<td>Office</td>
<td>30%</td>
<td>government; private-sector; courts</td>
</tr>
<tr>
<td>Retail</td>
<td>16%</td>
<td>high-street; department stores; centres</td>
</tr>
<tr>
<td>Primary Care</td>
<td>1%</td>
<td>health centres; surgeries; clinics</td>
</tr>
<tr>
<td>Hospitals</td>
<td>6%</td>
<td>all hospitals; medical research; nursing homes</td>
</tr>
<tr>
<td>Education</td>
<td>14%</td>
<td>schools; colleges; universities</td>
</tr>
<tr>
<td>Hotel</td>
<td>2%</td>
<td>all hotels and boarding houses</td>
</tr>
<tr>
<td>Sports</td>
<td>1%</td>
<td>gymnasiaums; pools; leisure centres; sport centres</td>
</tr>
<tr>
<td>Culture</td>
<td>1%</td>
<td>cinema; theatre; performance halls; museums; galleries; clubs</td>
</tr>
<tr>
<td>Community</td>
<td>11%</td>
<td>halls; religious buildings; centres; emergency services; community protection</td>
</tr>
<tr>
<td>Industrial</td>
<td>17%</td>
<td>transport terminals; factories; warehouses; storage</td>
</tr>
<tr>
<td>Other</td>
<td>2%</td>
<td>agriculture; unused buildings; freight handling</td>
</tr>
</tbody>
</table>

Table 2: Parameters of Prior Distributions of Energy Use Intensity per Building Type

<table>
<thead>
<tr>
<th>Primary Type</th>
<th>Median EUI in KWh/m²/year</th>
<th>Upper</th>
<th>Lower</th>
<th>Empirical Priors</th>
<th>Estimated Priors</th>
<th>Uninform. Priors</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>α</td>
<td>β</td>
<td>α</td>
</tr>
<tr>
<td>Office</td>
<td>267</td>
<td>125</td>
<td>565</td>
<td>1.4</td>
<td>3.0</td>
<td>6.5</td>
</tr>
<tr>
<td>Retail</td>
<td>329</td>
<td>160</td>
<td>685</td>
<td>1.2</td>
<td>3.0</td>
<td>4.0</td>
</tr>
<tr>
<td>Primary Care</td>
<td>303</td>
<td>115</td>
<td>570</td>
<td>1.7</td>
<td>2.4</td>
<td>11.0</td>
</tr>
<tr>
<td>Hospitals</td>
<td>480</td>
<td>194</td>
<td>1270</td>
<td>1.3</td>
<td>3.5</td>
<td>6.5</td>
</tr>
<tr>
<td>Education</td>
<td>221</td>
<td>105</td>
<td>637</td>
<td>1.3</td>
<td>3.4</td>
<td>1.8</td>
</tr>
<tr>
<td>Hotel</td>
<td>435</td>
<td>241</td>
<td>929</td>
<td>1.0</td>
<td>2.0</td>
<td>4.0</td>
</tr>
<tr>
<td>Sports</td>
<td>543</td>
<td>130</td>
<td>2462</td>
<td>1.1</td>
<td>4.4</td>
<td>4.9</td>
</tr>
<tr>
<td>Culture</td>
<td>303</td>
<td>79</td>
<td>1050</td>
<td>1.1</td>
<td>2.8</td>
<td>5.0</td>
</tr>
<tr>
<td>Community</td>
<td>326</td>
<td>108</td>
<td>794</td>
<td>1.6</td>
<td>4.3</td>
<td>6.5</td>
</tr>
<tr>
<td>Industrial</td>
<td>300</td>
<td>98</td>
<td>517</td>
<td>1.6</td>
<td>3.4</td>
<td>4.0</td>
</tr>
<tr>
<td>Other</td>
<td>85</td>
<td>50</td>
<td>400</td>
<td>4.0</td>
<td>4.0</td>
<td>4.0</td>
</tr>
</tbody>
</table>

RESULTS & DISCUSSION

To a number of reasons: (a) the local environmental characteristics may be very different in certain areas (heat islands), (b) the quality of the buildings in certain areas may be superior, (c) wealthier areas may have a higher concentration of EUI use to greater demand for services such as space cooling or (d) certain areas may have higher concentration of distributed or renewable technologies. In our current model we accommodate this variation also in $\varepsilon_k$. In future versions of the model, and with availability of a larger set of observations, we hope to accommodate deviations from this assumption explicitly.

The Bayesian analysis was carried out using WinBUGS. The number of MCMC iterations was carefully chosen to enable convergence of the Markov chains that constitute our synthetic samples of the posterior distributions. Indeed, with such a large number of parameters and so little information (12 unknowns and 33 observations), one expects a large initial time before stabilization of the random search. Also known as ‘burn-in period’, this time period was conservatively considered to be 20,000 iterations after some initial exploratory analysis and discarded from the analysis. For all three sets of prior choices, Figure 6 shows the posterior distributions derived after the burn-in period and for the subsequent 40,000 iterations. It also displays the three corresponding sets of priors in dashed line with the same color as their associated posteriors. These comparisons of prior versus posterior distributions are the main outcomes of this analysis.

If priors and posteriors roughly coincide, it means the observations did not help improve the estimation of the EUIs. On the other hand, if they differ, the shift in location and spread quantifies that we learn something from the data. It turns out that in our study we improve our knowledge of the EUIs only for the most prevalent categories, showing their dominant impact on total energy consumption. These are: offices, retail, community buildings, education, industrial buildings, and hospitals. For all these buildings posterior pdfs shift towards the upper limits of their EUI.

The analysis shows it is highly likely that offices in London consume more energy than the typical value estimated for UK. Figure 6 shows that the mean value of EUI is higher than 350 kWh/m²/year, and could be as high as 550 kWh/m²/year. As per CIBSE (2004), the typical EUI of an air-conditioned office is between 400-568 kWh/m²/year. 35% of 456 office buildings in the DEC register and 47% of 12,736 private-sector offices in the EPC database have a cooling system installed. Furthermore, owing to the cost of real estate, it is likely that offices in London have a higher density of occupants per m². This would naturally lead to higher EUI, since higher number of occupants would mean more power requirements.
Retail buildings are strongly skewed towards the right side of the plot, also indicating higher EUI than typical. Although posterior pdfs of hospitals, educational, community, and industry buildings shift to the right of their corresponding prior estimates, they have a wider (and more uniform) spread across the plausible range. This indicates a larger variability of EUI in these categories. Indeed, these categories represent a collection of several different sub-types. With more observations, further versions of this model will explore techniques for modeling them explicitly (eg. in a hierarchical structure supported by simulation-models of each representational sub-types).

The posterior distribution of the error term $\varepsilon_k$ is within the range 115-158 kWh/m$^2$/y. The prior distribution was wide, encompassing values close to zero as well as large values. Our analysis narrows down the error term to moderately large values. This distribution reflects all the uncertainties in the observations and the model (mentioned in the earlier section on error terms). Hence, it is natural to obtain such a large error term as a result of our analysis.

It is tempting to believe these outcomes even at this preliminary stage of model development. One can assume that because cities tend to be more dense, building types that provide services on a per person basis would tend to have a higher EUI than their national average. However, further improvements and tests of the model are needed before its outcomes are interpreted more precisely. More specifically, following issues need to be addressed as further extensions of the model: (a) More information is needed about how DECC compiles the energy statistics, and what forms of energy consumption are included in the dataset. Particularly, the categorization and reporting structures of non-building energy consumption (eg. communal lighting, infrastructure etc.) and process energy in the case of industrial buildings and large organizations. (b) More observations are needed, since the current model is able to learn about predominant building categories only. This could be done by increasing the unit of resolution to MLSOA with some techniques to handle half-hourly metered points, or by including LAs from other cities within the UK. (c) EUI associated with direct fuel consumption (heat) and indirect consumption (electricity) should be modeled separately. (d) Influence of inner city areas on variation of EUI in similar types of buildings should be explored, and (d) Prior estimates of EUI should be derived from simulations rather than empirical data. Indeed, a main driver of this work is to be able to quantify the impact of improvements in buildings by sector or by locality at the LA and at the city level. For this probabilistic simulation models of representational buildings will need to be developed for all the dominant types non-domestic buildings. A companion paper presented in the conference will illustrate a methodology for this through a representational model of school buildings in London.

REFERENCES


CIBSE 2004. Cibse guide f: Energy efficiency in
Figure 6: Calculated % Prior and Posterior Distributions of Energy Use Intensity for 11 Building Categories

buildings. Technical report, CIBSE.


